Testing Popular Visualization Techniques for Representing Model Uncertainty

Jeroen C.J.H. Aerts, Keith C. Clarke, and Alex D. Keuper

ABSTRACT: Many land allocation issues, such as land-use planning, require input from extensive spatial databases and involve complex decision-making. Spatial decision support systems (SDSS) are designed to make these issues more transparent and to support the design and evaluation of land allocation alternatives. In this paper we analyze techniques for visualizing uncertainty of an urban growth model called SLEUTH, which is designed to aid decision-makers in the field of urban planning and fits into the computational framework of an SDSS. Two simple visualization techniques for portraying uncertainty—static comparison and toggling—are applied to SLEUTH results and rendered with different background information and color schemes. In order to evaluate the effectiveness of the two visualization techniques, a web-based survey was developed showing the visualizations along with questions about the usefulness of the two techniques. The web survey proved to be quickly accessible and easy to understand by the participants. Participants in the survey were mainly recruited among planners and decision-makers. They acknowledged the usefulness of portraying uncertainty for decision-making purposes. They slightly favored the static comparison technique over toggling. Both visualization techniques were applied to an urban growth case study for the greater Santa Barbara area in California, USA.

Introduction

It has been demonstrated that simple and straightforward simulation models within a Spatial Decision Support System (SDSS) can be used to design land-use allocation alternatives (e.g., Grabaum and Meyer 1998). These models are usually implemented in the so-called "computational framework" of the SDSS (Aerts and Heuvelink 2002). Although model results do not always represent a complete overview of all possible allocation alternatives, they do supply a decision-maker with a quick, and to a certain extent, reliable overview of feasible solutions.

"Certain extent" refers to the uncertainty of the SDSS and, in this paper, to the uncertainty of an urban growth model called SLEUTH (slope, land use, exclusion, urban extent, transportation, and hill shade) developed for use within an SDSS environment (Figure 1; Aerts 2002; Clarke and Gaydos 1998). Uncertainty in this context may be referred to as uncertainty in the input data and model formulations (e.g., Cleaves 1995; Heuvelink 1998; Ehlschlaeger 2002). Managing uncertainty for decision-making issues involves quantifying uncertainty, and having a thorough understanding of how uncertainty propagates through different operations in the model. Moreover, it involves learning how to make a decision when uncertainty is present and communicating uncertainty to decision-makers. Researchers have responded to these issues by developing numerous concepts and techniques that can be used to quantify uncertainty and its propagation for decision-making problems (e.g., Hunter and Goodchild 1995; Heuvelink 1998).

It is commonly agreed that visualizing uncertainty is a critical aspect of using spatial data and models within decision-making problems, such as land allocation problems (Armstrong et al. 1992; Goodchild et al. 1994; Hunter 1999). In addition there are a considerable number of visualization techniques available to communicate uncertainty of GIS (geographic information system) data and models to users (MacEachren 1994; MacEachren and Kraak 1997; Pang et al. 1997; Beard and Buttenfield 1991; 1999). There is, however, little literature on the *effectiveness* of visualizing uncertainty in this context (Nedovic-Budic 1999; Drecki 2000). Research reports the importance of understanding user requirements for visualizing uncertainty, but notes the exclusion of human factors in most exploratory visualization research. Relevant and comprehensive studies have been conducted by Evans (1997), Leitner and

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Buttenfeld (1997; 2000) and Watkins (2000). They describe experiments for evaluating visualization techniques for portraying uncertainty and emphasize the need for further empirical research to test visual variables and their usefulness for depicting data quality.

Although we acknowledge all forms of uncertainty as important, we will focus in this paper on the visualization of model uncertainty—more specifically the visualization of spatial (GIS) results produced by the urban growth model SLEUTH. This model has been designed to aid decision-makers in the field of urban planning and fits into the computational framework of an SDSS (Figure 1). Our main goal was to derive evidence that uncertainty representations can be considered valuable information in decision-making issues. An innovative aspect of this research was to use a web-based approach to convey the survey and to involve real planners and decision-makers in the evaluation.

The main objectives of this paper are to:

- Apply two popular visualization techniques to SLEUTH results—static comparison and toggling;
- Develop a web-based survey for conveying and evaluating the visualization techniques; and
- Analyze the results with respect to the effectiveness of the visualization techniques for decision-making issues.

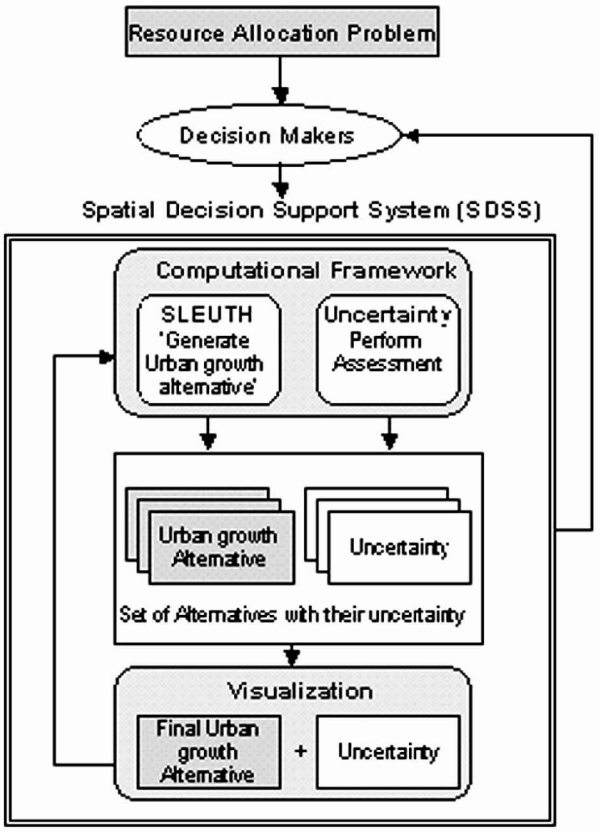

Figure 1. SDSS structure with a decision framework and supporting techniques.

Urban Growth Modeling

The SLEUTH model, formerly the Clarke Cellular Automaton Urban Growth Model, is capable of predicting the dynamics of urban growth (e.g., Clarke and Gaydos 1998; Silva and Clarke 2001). The basic urban growth procedure in SLEUTH is a cellular automaton, in which urban expansion is modeled in a GIS environment. Cellular Automata (CA) are dynamic mathematical systems based on discrete time and space and are particularly well suited to model dynamical systems (for more CA details, see, e.g., Schatten 1999).

At each time step, a series of urban growth rules is applied to all cells, and each cell's land use is updated (Candau et al. 2000). Urban growth rules in the model are bounded by two aspects of suitability. The first is defined by an *exclusion layer,* which defines areas where urban growth may not occur. This layer excludes, for example, water bodies and nature reserves. The second aspect refers to *slope* as steeper slopes above 21 percent are less likely to be urbanized. Different combinations of land suitability are compiled in scenarios, which reflect different measures planners may take. For instance, a commonly employed exclusion measure is the implementation of an urban growth boundary, beyond which urban growth is prohibited. This can be combined with the exclusion of urban growth from all preserved areas, agricultural lands, and parks.

In this paper, we use the model results for a case study area in Santa Barbara, California (Figure 2). The main reason for choosing this area is that the model has been intensively calibrated on the basis of historical data, and that these results are provided with uncertainty information. We use the "Agricultural" scenario where *only* land transition from agricultural land to urban land may occur. Other non-urban areas are excluded from urbanization. Although planners in the Santa Barbara region have implemented an urban growth boundary, we ran the model without any specific boundary line, and urban growth exclusions only referred to water bodies and parks.

An example of a model result for the Santa Barbara area is depicted in Figure 3. The results are represented in maps depicting urban versus non-urban, ocean, and not-classified (mask) cells. Cells depicting urban growth are provided with a certain probability (read: uncertainty), since the urban growth map is

Figure 2. The Santa Barbara case study area.

the cumulative result of 100 equally probable Monte Carlo runs. Hence, a single urban growth cell with a value of "1" implies that the model simulates urban growth for that cell only *once* across a total of 100 simulations. The urban growth cells in Figure 3 are cells with values between 1 and 100.

Visualizing Uncertainty

During the last 10 to 15 years there has been an increasing demand for appropriate uncertainty information for geographic data and models (Beard and Buttenfield 1991; Davis and Keller 1997; MacEachren and Kraak 1997; Drecki 2000). The need to understand uncertainty is of particular importance when data and models are used in the decision-making process, where variation in results may have profound implications. In this context, Hunter (1999) writes that "decision-makers using GIS information are often unaware of the potential traps that can lie in the misuse of their data." And, "the lack of uncertainty information has the potential to harm the reputations of both individuals and agencies, and public's confidence in them." Other authors point out that visualization research has ignored uncertainty visualization, which is partly due to problems with defining uncertainty itself as well as the lack of a general visualization standard (Pang et al. 1997; Paoli and Bass 1997; Bastin et al. 2000).

Despite possible ignorance of uncertainty visualization in research there is a considerable number of visualization techniques available to communicate the uncertainty of GIS data to users (MacEachren 1994; MacEachren and Kraak 1997; Kraak 1999). Most of these techniques use Bertin's (1983) graphical framework as a basis and explore new visual variables. Bertin (1983) describes an extended set of visual variables to portray information, such as position, size, value, texture, color, orientation, and shape. Among these variables, "the strongest acuity in human visual discriminatory power relates to varying size, value and color" (Buttenfield and Beard 1994). Simple approaches for visualizing uncertainty are described by MacEachren (1992; 1994). MacEachren (1994) suggests, for example, a "side by side" technique, also known as "static comparison" (see also Van der Wel et al. 1994; Drecki 2000). Other straightforward techniques are "differencing" and "toggling" (MacEachren 1994; Pang et al. 1997). In a static comparison, data are presented in the left portion of the display and data uncertainty in the right portion. Toggling is a technique to manually or automatically swap between data and data uncertainty. The way to present uncertainty depends on the visual variables used. For instance, MacEachren (1994) used color lightness and color saturation for visualizing uncertainty, for both static comparison and toggling techniques. Other variables used in static representations include blending, focus and color transformation (Drecki 2000).

Using a bivariate or multivariate map is a combined technique. The technique requires overlay of contrasting visual variables in one visualization (Beard and Buttenfield 1999). The disadvantage of this method is the possible "overload" of information within the representation and, therefore, the decreased ability of the user to understand the display and to discriminate uncertainty from other data (Van der Wel et al. 1994; Van der Wel and Van der Gaag 1998; Buttenfield and Beard 1994). Animation techniques involve the use of time as a variable for sequencing of multiple realizations of data reliability. GIS-based animation methods for visualizing uncertainty were described by Ehlschlaeger and Goodchild (1994) and Ehlschlaeger et al. (1997). Other methods find their origin within remote sensing analysis and classification (Fisher 1994; Bastin et al. 2000). Finally, recent developments in the portrayal of uncertainty refer to 3D visualization techniques and the use of "glyphs." Examples of such applications can be found in Pang et al. (1997), MacEachren et al. (1999), and Clarke et al. (2000).

User requirements, human perception, and user experience are all examples of human factors that largely determine whether visualization of uncertainty can be considered as effective (MacEachren 1992; 1994). For instance, a decision maker working in a planning department probably requires different visualizations of map uncertainty for his work compared to a GIS professional in the same department. While this reveals a need for a survey that evaluates visualization techniques for representing uncertainty, quantitative determination of

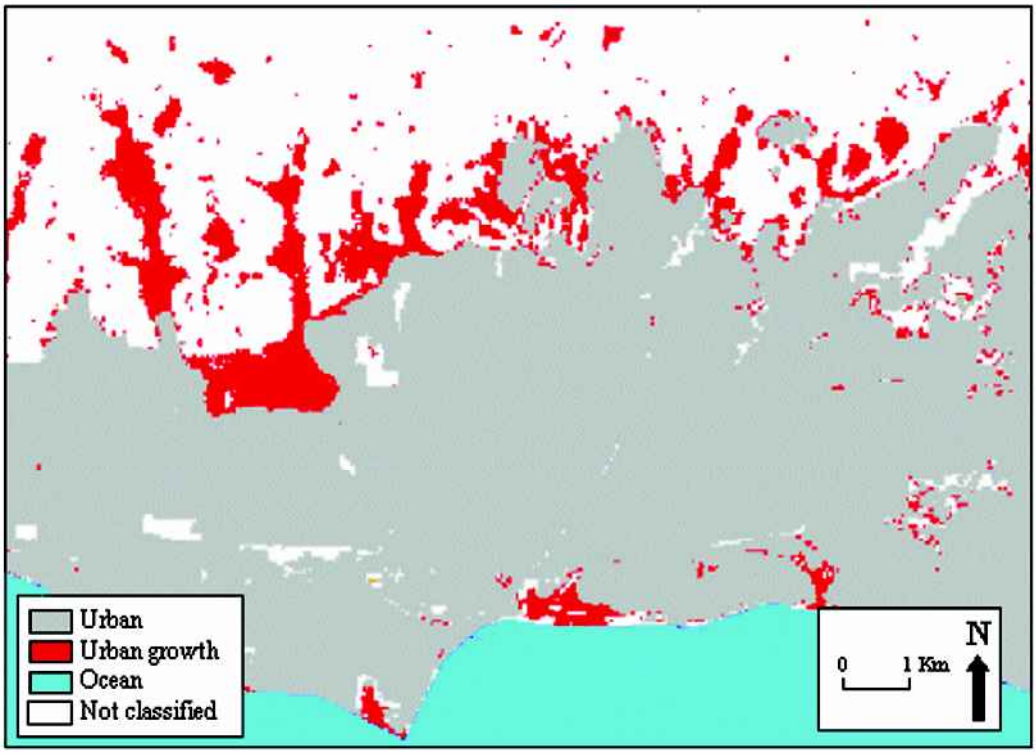

Figure 3. Urban growth for the year 2050 simulated by SLEUTH for the Santa Barbara, California, area.

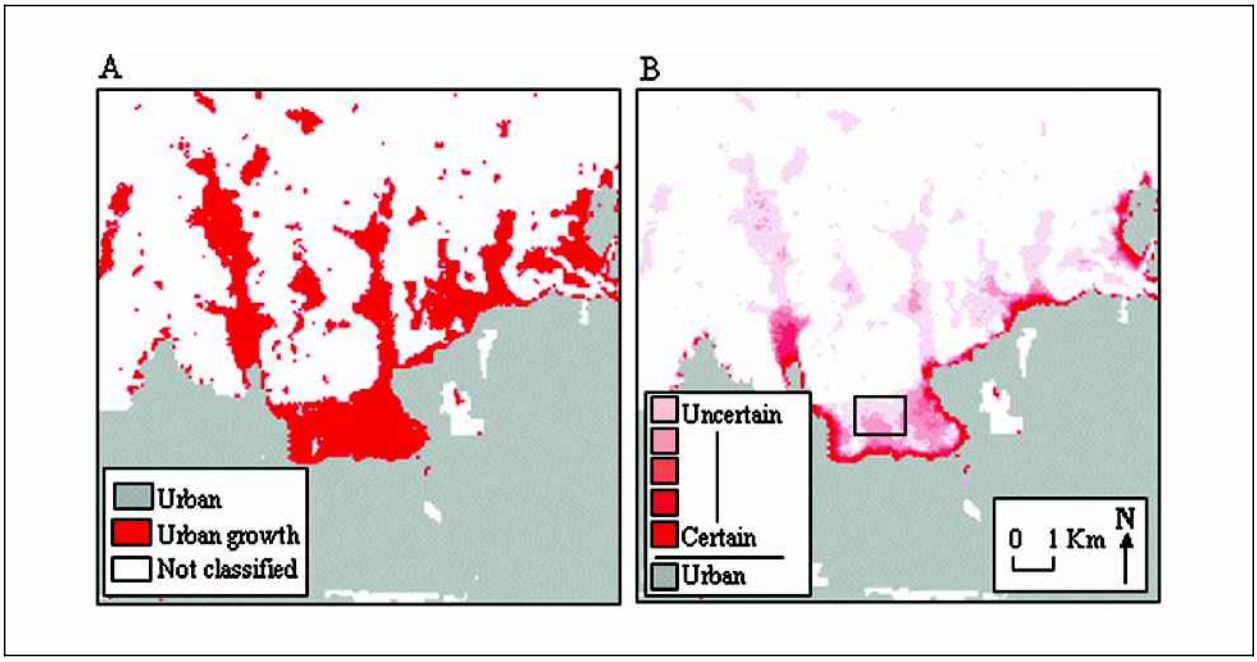

Figure 4. Static comparison technique with a model result (A) and its uncertainty (B). The black rectangle was used as a reference area during the survey to ask the participants whether they could recognize uncertainty in urban growth within the black rectangle.

what methods are appropriate for a specific user and use is not an easy task: it can *only* be derived by conducting a survey (Armstrong et al. 1992; Drecki 2000).

Examples of visualization surveys can be found in Brewer (1999a; 1999b) who presented empirical tests for the use of different color schemes representing different geographical phenomena. MacEachren

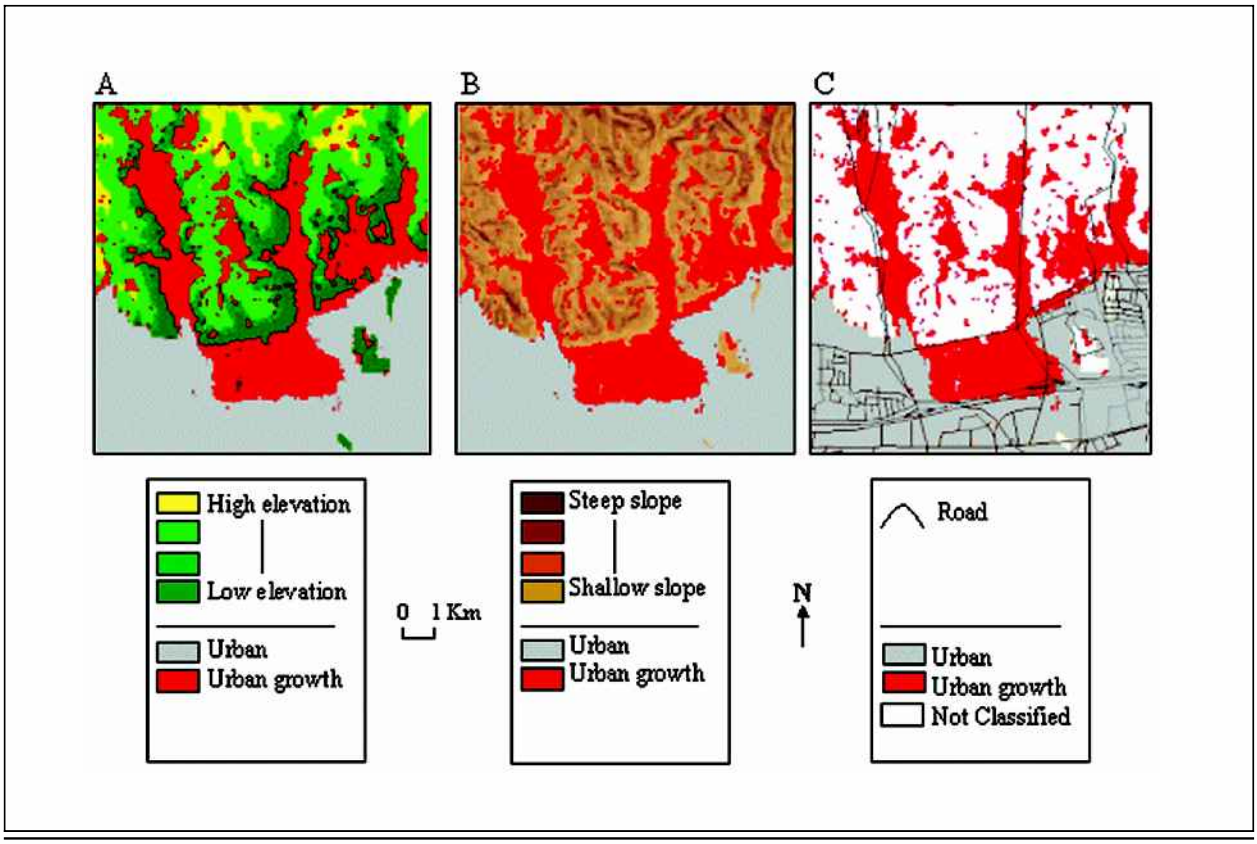

Figure 5. Urban growth simulation presented with different background information layers: Elevation (left), slopes (middle), and roads (right).

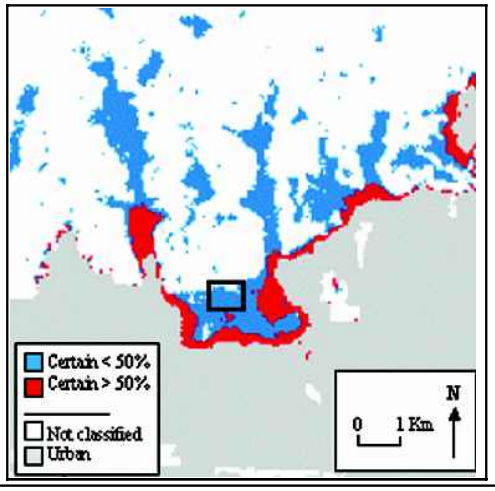

Figure 6. Presenting uncertainty using a bicolor scheme. The black rectangle points to a case study area used in question 6.

(1994) developed the reliability visualization system (RVIS), which supports viewing the reliability of data using a set of visualization techniques, such as static comparison and combined displays. Crossland et al. (1995) tested the effectiveness of visualization techniques within an SDSS, but without involving "real" decision-makers. Important contributions were made by Leitner and Buttenfield (1997; 2000) who describe experiments that investigated the impact of data quality on site decisions. Various cartographic variables were used, such as color value, saturation, and texture to create multiple versions of site maps. Evans (1997) conducted a survey on visualizing uncertainty in remote sensing imagery, and Watkins (2000) discussed a comprehensive experiment for evaluating uncertainty within an SDSS for combat simulations used by the military services.

Web-based Survey Design

Based on basic graphical techniques described by MacEachren (1994) and the experience gained from surveys conducted by Evans (1997), Watkins (2000), and Leitner and Buttenfield (1997; 2000), we applied two relatively popular methods for visualizing uncertainty, using color lightness as the only graphical variable. Color lightness has been identified as one of the most obvious variables to portray uncertainty (MacEachren 1994). The first method applied was the "static comparison" technique where a model of the result and its uncertainty are presented in side-by-side images.

The second was "toggling" where the model result and its uncertainty are sequenced in an animated loop at a very slow time interval of four frames per second (Evans 1997). Both techniques were applied to the results of the SLEUTH model.

In addition to the approach described by Evans (1997), who mainly used geography students as subjects, this survey aimed at involving planners and decision-makers. A web site was developed in order to quickly access a large group of participants for the survey. The web site contained a series of information sheets explaining the goal of the research, a description of the case study area, an explanation of spatial uncertainty, and background information on visualization of uncertainty. Each participant was personally invited to participate. The total group of subjects consisted of more or less equal numbers of persons with visualization experience ("experts") and without such experience ("novices"). A series of questions and statements was formulated to derive a quantitative response from the participants as to the effectiveness of the two visualization techniques.

In order to derive independent answers with respect to each of the two visualization methods, the survey was split into two separate websites, each containing questions about only one of the two visualization methods. Accordingly, the participants were divided into two groups. Only in the last question were participants notified of the other technique, and asked to directly compare the two methods. Much time was invested in designing the survey to avoid leading questions and anticipating the fact that the participants learn during the survey (Rosenthal and Rosnow 1991; Fowler 1993).

Due to the nature of this research, we applied the following measures to maintain user comprehension and objectivity throughout the survey:

- Variations in color ramps and background information were kept constant across both techniques;
- Questions were posed in the form of statements to which participants could respond by indicating how much they agreed or disagreed with each statement (Appendix 1); and
- Participants were asked to imagine that they were making a decision and formulate their answers accordingly.

The complete survey took approximately ten minutes. Given the international composition of our team, many of the subjects came from outside the U.S.

Survey Overview

This section describes the survey as it was rendered on the internet. The first page of the survey site carried brief statements of the goal and the structure of the research. Next the case study was described, followed by a questionnaire where the visualization techniques were tested.

The Santa Barbara Case Study

The case study focused on urban growth predictions, simulated with SLEUTH, to the year 2050 for the greater Santa Barbara area, California, USA. Figure 2 shows the study area depicted within a black rectangle. To the north of Santa Barbara city is the Los Padres National Forest, which is mainly a steep mountainous terrain covered with mixed vegetation of chaparral, grassland, and minimal agriculture. Mountains rise to about 1300m (4000 ft) barely 8 km from the coast. To the south of Santa Barbara is the Pacific Ocean. Near the ocean and the mountains, geographic circumstances are largely unfavorable for significant urban growth in the area. Most of the urban growth is thus expected in the western and eastern parts of the current urban area.

Urban growth projections by the California State Department of Finance (DOF) estimate a statewide increase in population from 35 million to 50 million for the year 2030. Despite geographical limitations, it is expected that the population of Santa Barbara County will increase by almost 60 percent (from 414,000 to 658,000 people by 2030)Ł at an average rate of about 1 to 2 percent a year (SBC 2000).

The strict geographic boundaries on one side and the growth projections on the other side fuel a controversy among stakeholders in the region. The discussion centers about where to develop new urban areas without threatening the environment, and how to maintain a level of affordable housing under conditions of rapidly increasing property prices. The basic idea is to develop SLEUTH into a full-capacity SDSS to facilitate discussion on urban growth by presenting stakeholders with urban growth alternatives under different scenarios. A prototype of this system is on-line at http://zenith.geog.ucsb.edu/scenario.

Questions and Statements

Questions 1a, 1b, and 1c were asked to obtain information about the participants and their professional experience. Each participant was asked to give their "age," "sex," and "experience." Under "experience" participants could choose between "planning," "decision support," "visualization," "GIS" and "other experience." Only *one* field could be selected (Appendix 1). A subject was

labeled as a novice when he or she checked "other experience" in question 1c.

Questions 2 and 3 helped evaluate the participants' ability to recognize spatial features on a map and aerial photographs. Question 2 shows a result from the SLEUTH model where urban growth is depicted. Survey participants were asked to what degree urban growth is discernable. In question 3 participants were presented with an aerial photograph of Bishop Ranch, an area in the western part of Santa Barbara that might be developed into an urban area, and asked whether they could estimate, from the aerial photograph, the degree of urbanization forecast around Bishop Ranch.

In questions 4a and 4b, the uncertainty of the SLEUTH model was visualized using either "static comparison" or "toggling." Urban growth was depicted in red, while current urban areas were depicted in gray (Figure 4). Different shades of red depicted different levels of uncertainty in the model simulation. Light red depicted areas of uncertain urban growth, while the darker reds indicated areas of certain urban growth. No further background information was given except for legends explaining the colors in the visualizations.

Similar to experiments by Evans (1997) and Leitner and Buttenfield (1997; 2000), participants were asked to respond to statements 4a and 4b, while actually making a decision. They were asked to imagine being responsible for writing a report on future urban growth for the area in the black rectangle Figure 4), and whether they could make simple approximations (50 percent, 75 percent, etc.) about the amount of uncertainty associated with simulated urban growth in the black rectangle.

In question 5, the visualization used in question 4 was combined with three types of background information layers: road elements, elevation, and slope. The participants were asked to imagine discussing with other people where future urban growth is likely to occur, while describing the environment surrounding the urban growth areas. The question focused on which of the three "background maps" provided the user with the most valuable information for describing urban growth and its surrounding landscape to others (Figure 5).

In question 6 two figures with similar uncertainty in urban growth were shown, but using different color schemes. One image used shades of a single hue—red—to depict uncertainty. The other image used a bi-color scheme to depict different levels of uncertainty: red for certain urban growth and blue for uncertain urban growth. Participants were asked to imagine writing a report on future urban growth for the area within the black rectangle (Figure 6) and compare the single-color and bi-color visualizations.

In question 7, the two visualization techniques (static comparison and toggling) were evaluated "head to head." This was the only part where the participants were notified of the existence of another visualization technique, and the question explicitly required a preference for only *one* of the visualization methods used in the survey.

The last question, question 8, comprised a series of exit questions aimed at determining whether the survey was easy to comprehend and whether visualization of uncertainty is a valuable technique for decision-makers dealing with planning issues. The complete set of questions and statements is presented in Appendix 1.

Results

Of the 93 invited participants, 66 returned a complete form via the internet, bringing the total response rate to 71 percent. The general reactions to the survey were positive, and almost all participants understood the goal and (possible) role of uncertainty visualization within the context of spatial decision-making. This is illustrated by the answers to the exit questions 8a, b, and c (Figure 7). Slightly over 80 percent of all participants considered the survey "almost completely" or "completely" understandable. Novices had somewhat more difficulty understanding the survey than did experts. Note that the designation of an "expert" is subjective, and that we defined a novice as a participant who selected the "other expertise" category in question 1c (Appendix 1). About 56 percent of the participants were classified as expert. A Chi-square test was used to analyze responses for the two visualization methods used and between experts and novices. Table 1 shows all test results with their associated p values. Figure 7 illustrates a comparison of the two visualization methods, while Figure 8 compares the results across novices and experts.

Most participants recognized urban growth as simulated by the SLEUTH model in question 2. More than 33 percent of the experts responded they could recognize urban growth "completely" compared to 22 percent of similar observations made by novices (Figure 8). Hence, experts interpreted the spatial results somewhat more easily than novices did, although this was not statistically significant ($p=0.30$). The responses to question 3 indicate that most participants were able to identify urban areas around Bishop Ranch. More than 60 percent categorized the area around Bishop Ranch

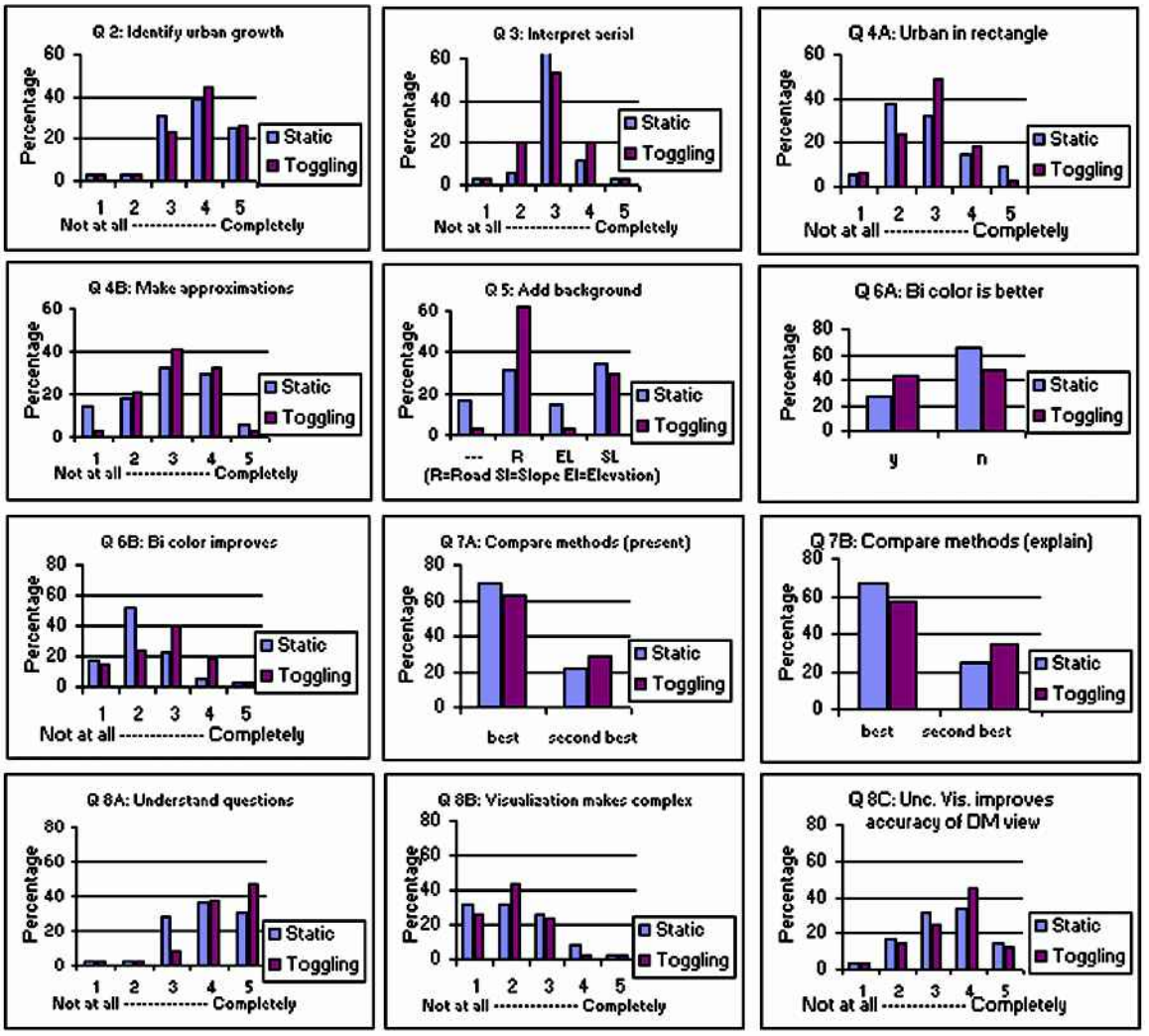

Figure 7. Experiment results per group, evaluating static comparison (method 1) and toggling (method 2). Categories 1 to 5 refer to the level of agreement with a statement (see also Appendix 1).

as "somewhat" urbanized, which was expected. It was thus concluded that all participants were able to recognize relevant spatial patterns necessary for interpreting visualizations of uncertainty.

All participants recognized uncertainty in projected urban growth, irrespective of the visualization method used (questions 4a,b; Figure 7). Their responses indicated that the marked area was "slightly" to "somewhat" likely to become urban in the future. Chi-square test results indicated that the response patterns for the two methods were significantly different in question 4b (p=0.001), suggesting that the two groups did not interpret the displays in the same manner. Participants evaluating the static comparison method estimated the uncertainty more accurately (38 percent responded "slightly") than did those evaluating the toggling method (25 percent responded "slightly" in question 4a; Figure 7).

Question	Expert vs. Novice		Static vs. Togling	
	CH^2	(*p*)	CH^2	(*p*)
2	2.57	*0.30*	0.45	*0.88*
3	3.45	*0.18*	5.38	*0.05*
4a	3.16	*0.18*	3.19	*0.06*
4b	8.24	*0.00*	3.48	*0.00*
5	2.96	*0.11*	9.53	*0.00*
6a	0.15	*0.88*	2.14	*0.34*
6b	5.94	*0.02*	7.07	*0.00*
7a	4.53	*0.03*	0.50	*0.89*
7b	0.64	*0.74*	0.93	*0.74*
8a	3.77	*0.17*	4.64	*0.00*
8b	1.26	*0.50*	1.86	*0.23*
8c	5.37	*0.01*	0.95	*0.70*

Table 1. CHI Square test results and *p* values by question.

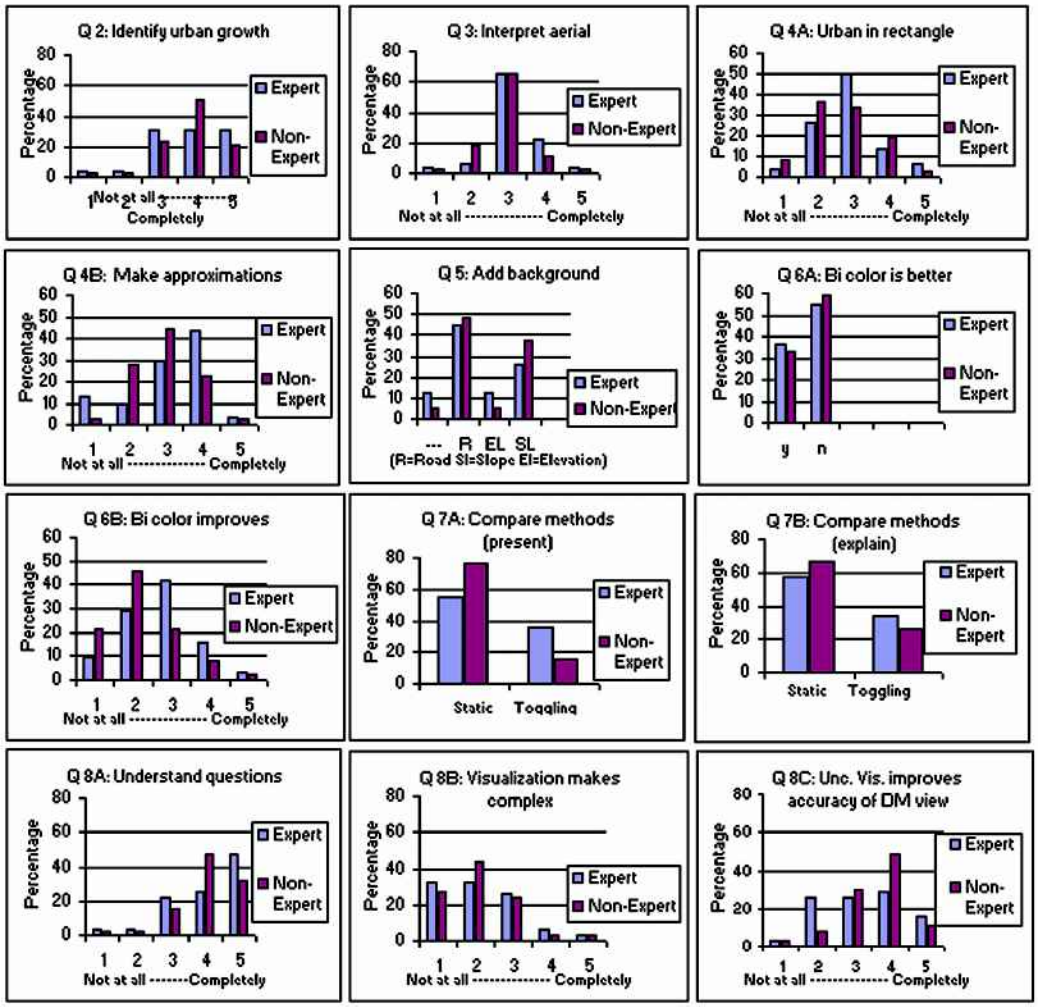

Figure 8. Evaluation results by level of experience—Experts versus novices. Categories 1 to 5 refer to the level of agreement with a statement (see also Appendix 1).

Some participants noted that elevation and slope information increased the complexity of the display, while vector-based road information did not.

In question 5, most participants were for including roads (50 percent) or slopes (31percent) as background information. Apparently, those evaluating the toggling method (Figure 7) were more likely to prefer road and slope information rather than elevations. Participants evaluating the static comparison, had less pronounced preference for roads and slopes, choosing "no background" and "elevation" in 18 percent and 15 percent of the cases, respectively (Figure 7). The urban growth procedures in the SLEUTH model are driven by slope, with higher slopes decreasing the chance of urbanization. This information was not conveyed to the participants.

Concerning the single color versus bi-color scheme, the static and toggling groups produced significantly different responses in question 6b ($p=0.002$). Slightly more than 60 percent of the static comparison group preferred the single-color scheme to the bi-color scheme. Participants evaluating only the toggling method almost equally preferred the single and bi color scheme. Significant differences in responses also occurred between experts and novices ($p=0.023$); 43 percent of all experts in both groups indicated that they saw a potential for bi-color schemes for portraying uncertainty, despite preferring the single color scheme. Only 22 percent of the novices responded similarly (Figure 8). Conceptual differences may exist that preclude the comparison between single- and multiple-color cartographic methods. We argue that in both cases, only one color carried the uncertainty information, so comparison was indeed possible.

Seventy-two percent of all participants preferred the static comparison technique over the toggling technique, and some noted that they were annoyed by the toggling technique (questions 7a, b). The preference for the static comparison was, however, less pronounced for those who only evaluated the

toggling technique. This group seems to have been more accustomed with the toggling technique, and, consequently, valued the technique more highly than static comparison. Sixty percent of the experts preferred static comparison compared with 40 percent for toggling, while as many as 83 percent of novices preferred static comparison versus 17 percent for toggling ($p=0.028$).

The majority of respondents (64 percent of the static comparison group and 75 percent of the toggling group) responded that the representations increased the complexity of the display "not at all" or "slightly" (question 8b). The responses to question 8c indicated that more than 70 percent of all participants agreed "almost completely" or "completely" with the statement that uncertainty visualization improves the decision-makers' view, analyses, and model simulations.

Discussion and Conclusions

In this paper, we focused on the visualization of uncertainty in spatial model results produced by the urban growth model SLEUTH (Clarke and Gaydos 1998). The model was applied in a case study simulating urban growth in Santa Barbara, California, in order to aid decision-makers in urban planning. A survey on the internet was developed to evaluate the effectiveness of two popular techniques for visualizing uncertainty of SLEUTH results—static comparison and toggling. The web-based approach was selected because it offers quick access to subjects all around the world.

Given the number of responses it can be concluded that a web-based approach lowers the threshold for subjects to participate. Many potential users are connected to the internet and probably fill out various questionnaires while surfing the internet during their regular work time. It was remarkable how quickly our participants filled out the questionnaire and sent back their answers. We attempted to avoid a biased result by carefully selecting the participants and questions. This research involved more planners and decision-makers than did other studies (e.g., Evans 1997). We also spent considerable time formulating the questionnaire, so as to avoid "leading" questions while recognizing that participants will learn during the survey. Our experience is that a web-based survey is a convenient and fast medium to conduct visualization experiments and seems to be a promising environment for additional research in this area. This study has shown that some differences exist between novices and experts in terms of their preferences for uncertainty visualization, although these are not always significant.

Similarly to Leitner and Buttenfield (1997; 2000), we found that the majority of participants indicated that embedding uncertainty information (depending on the visualization methods used) tends to clarify rather than render a graphical display more complex. Experts, as well as novices, responded positively to both techniques and considered the survey to be comprehensible. We concluded, as did Evans (1997), that static comparison and toggling (although the latter was somewhat less preferred by the participants) can improve the efficiency of spatial decision-making for land allocation issues. Toggling is helpful, yet sometimes annoying. Color lightness as a graphical variable was found to be a powerful variable for representing uncertainty, which is in line with findings in other research (Buttenfield and Beard 1994; MacEachren 1994; Leitner and Buttenfield 1997; 2000).

While stated preference for uncertainty displays is important—since much of cartography is aesthetic as well as informative—future research must further determine whether displaying uncertainty information leads to users arriving at different conclusions about the data. Do different visual depictions of uncertainty result in different interpretations of the data in question? In order to answer this, future research must compare other and new display types measuring responses to similarly structured tasks or problems. An experimental design that varies data user experience and display type but holds the task as a constant should demonstrate whether measurable differences exist between the two variables.

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Appendix 1

Static Method Evaluation Questionnaire

Please answer the following questions before proceeding. Please complete all STEPS in sequence, and respond to each statement or question. You may add additional comments at the end of the questionnaire. Submit your completed survey form using the "Submit Survey" button.

Question 1
1a. Your age?
1b. Male or Female?
1c. Your primary work experience is in (check only one box): Urban planning (), Map visualization ( ), Decision support ( ), GIS ( ), None of the above ( ).

Question 2
This image (Figure 3) shows a result of the SLEUTH model. It depicts the simulated new urban areas for the year 2050. Answer: I can identify the areas of urban growth—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

Question 3
This aerial photograph shows the Bishop Ranch (white rectangle) and the UCSB coastal area (white circle). Answer: Bishop ranch is bordered by urban areas—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

Question 4
The image on the LEFT depicts the simulated urban growth areas in red (Figure 4). These areas were calculated by the SLEUTH model. The image on the RIGHT depicts the uncertainty of this simulation. The different shades of red depict different levels of uncertainty in the prediction. Light red depicts areas of uncertain urban growth, while the darker reds depict areas of certain urban growth. Imagining you are responsible for writing a report on future urban growth for the area within the black rectangle, please answer the following questions:

4a: The area within the black rectangle is likely to become urban in the future—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

4b: I can make simple approximations (50%, 75%, etc) about the amount of UNCERTAINTY associated with simulated urban growth in the black

rectangle—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

Question 5

These three images depict the same uncertainty as in Step 4 (Figure 5). However, each uncertainty map is combined with different background information. The image on the left includes elevation information. The center image includes slope angles. The image on the right depicts road elements. Imagine you are discussing with other people where future urban growth is likely to occur and you wish to describe the environment surrounding the urban growth areas. Which of the three 'background maps' provides you with the most valuable information for describing where growth will occur?

Answer: In order to discuss urban growth and its surrounding landscape, I would add—1. None of these maps would help; 2. Roads; 3. Elevation; 4. Slopes.

Question 6

The two figures show similar uncertainty in urban growth but use different color schemes. The image on the LEFT uses shades of a single color—red to depict uncertainty. The image on the RIGHT uses different colors—red and blue—to depict different levels of uncertainty (Figure 7). Imagine your task is to write a report on future urban growth for the area within the black rectangle.

6a: The image that uses different colors to depict variations in uncertainty is better at helping me describe the area of future urban growth—1. Yes; 2. No.

6b: Using different colors to represent uncertainty (such as in the right figure) improves the visibility of the uncertainty—1. Not at all; 2. Not really; 3. Somewhat; 4. Almost completely; 5. Completely.

Question 7

Consider these two different visualization methods for representing uncertainty in urban growth. The left method is a STATIC visualization method as already shown in the previous steps. The right method uses TOGGLING techniques to depict uncertainty. Please answer the following statements by comparing the different visualization techniques:

7a: Uncertainty is best presented in—1. Method 1, left; 2. Method 2, right.
7b: If I had to explain uncertainty in urban growth to members of a planning board and the general public, I would choose—1. Method 1, left; 2. Method 2, right.

Question 8

8a: The idea of visualizing uncertainty as presented in the questionnaire was easy to comprehend—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

8b: Uncertainty visualization makes the display of planning information too difficult and complex to use—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.

8c: Uncertainty visualization would improve the accuracy of decision-makers' views, analyses and predictions—1. Not at all; 2. Slightly; 3. Somewhat; 4. Almost completely; 5. Completely.